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Electro-mechanical Parameter Determination of Induction Motor Using Generalized Regression Neural Network

Abstract: - Overheating of electrical components in household appliances might occur sometimes due to short circuit faults. Degradation of electrical equipment may take place due to voltage fluctuations. Hence, an electrical protection system is required for electrical equipment. A detection system can monitor and capable of providing specific protection. This project is aimed to develop a fault detection and clearance system which will monitor , detect and protect equipment from electrical faults. A protective system has been designed using Arduino, that acts as a microcontroller with the help of current sensor, voltage sensor , IR and temperature sensor embedded into it. If current, voltage, speed and temperature values exceeded the preset values, the device begins to realize that some abnormal conditions or faults took place in the equipment. With the help of relay and Arduino, equipment was protected from fault. The generalized regression Neural network (GRNN) model was trained using the measured data. The proposed GRNN model had been tested with new data sets using MATLAB-SIMULINK. The test result reveals that GRNN model can effectively determine the electro-mechanical parameters of induction motor.

Keywords: Induction motor, Arduino, Voltage sensor, Current sensor, speed sensor, temperature sensor, GRNN

I. INTRODUCTION

An electrical fault is a condition in the electrical system that causes failure of the electrical equipment. Over current flow takes place when fault occurs, it creates a very low impedance path for the current flow. This results in a very high current being drawn from the supply, causing tripping of relays, damaging insulation, and components of the equipment. It sometimes causes danger to operating personnel. Fault occurrences can also cause shocks to individuals. Severity of the shock depends on the current and voltage at fault location and even may lead to death. Heavy current due to short circuit faults result in the components being burnt completely which leads to improper working of equipment or device. Sometimes heavy fire causes complete burnout of the equipment. Short circuit causes flashovers and sparks due to the ionization of air between two conducting paths which further leads to fire. Fault detection and protection systems are crucial components of electrical equipment, playing a vital role in ensuring safety and reliability. These systems monitor electrical parameters and detect anomalies that could lead to faults or equipment damage. With the help of Arduino, sensors, and relay, it detects and protect the device from the faults.

Sumit Narwade1 etal [1] have explored various faults, including bearing damage and unbalanced voltage supply, using vibration and motor current signature analysis. V. Bolshev etal [2] have developed a monitoring system using Arduino nano V3 AT mega 328 to enhance power supply reliability and quality. It emphasizes the necessity of monitoring parameters on both sides of switching devices and proposes a functional circuit to monitor power outages and voltage variations. An algorithm is used to detect emergency modes within the consumer's network. Laboratory tests validate the prototype's effectiveness in monitoring electrical parameters. Overall, this research offers a promising solution to improve power supply reliability and quality through advanced monitoring systems. Santosh Kumar Bisoriya etal [3] have developed a cost-effective system for safeguarding induction motors from various faults such as overvoltage, undervoltage, overcurrent, overload, excessive heating, and crawling. The system employed sensors to monitor parameters like speed, temperature, current, and voltage

Artificial intelligence (AI) techniques are used to solve electrical engineering problems. The advantages of AI techniques are simple calculation and lesser computation time. AI techniques provide accurate results. Researchers have used Neural networks (NN) techniques to extend prediction models for mechanical properties of materials. GRNN requires only a portion of the training samples than a back propagation neural network. GRNN is advantageous due to its capability of converging to the basic function of the data with a small number of existing samples. This make the GRNN as a constructive tool for the problems with insufficient data. Instead of training weights, the GRNN assigns the target value directly to the weights, w_{ij}, from the training set associated with input training vector and a component of its corresponding output vector [4].

For instance, Haque and Sudhakar [5] predicted the fracture toughness in various types of steel and the consequence of heat treatment on mechanical properties. Compared with the standard feed forward neural networks, GRNN has a relatively simple and static structure [6].The GRNN model is simpler and computationally faster. Also the GRNN model does not need an iterative training procedure like the MLP-ANN model. It trains rapidly without encountering the problems of local minima that characterize standard feed forward network [7, 8]. Das Merces Machado et al [9] used GRNN to interpolate not stored points of the characteristic

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curve. Goulermas et al [10] proposed a novel algorithm for function approximation that extends the standard GRNN. Rutkowski [11] proposed a new class of GRNN working in non-stationary environment., which can be able to follow changes of the best model, i.e., time-varying regression functions. Herein the effort have been made to employ GRNN method to determine the electro-mechanical parameters of induction motor.

II. FAULTS IN SINGLE PHASE INDUCTION MOTOR

In normal conditions, an electrical system operates at nominal current and voltage values. During an electrical fault, the current and voltage level diverges from the nominal value into the abnormal value. An electrical fault is a condition in which abnormal levels of voltage and current are introduced into the electrical system. The abnormalities in an electrical system that causes unwanted current is called an electrical fault. The current in such a condition is called fault current. The electrical fault reduces the insulation strength of the conductors causing a short circuit and damaging the equipment and appliances. It can create a short circuit, open circuit, overcurrent, undervoltage, overvoltage, reverse power and unbalance in the phases. There are different types of faults in electrical systems classified based on their condition. They are transient fault, persistent fault, over current, under voltage, overloading and overvoltage.

Single-phase induction motors are widely used in various applications due to their simple construction, self-starting capability, and low maintenance requirements. However, they are susceptible to faults that can affect their performance and reliability. The common faults in single-phase induction motors are stator winding fault, rotor fault, starting capacitor fault, mechanical fault and thermal fault.

A. Stator winding fault and rotor fault

Stator winding fault can be caused by insulation breakdown, overheating, mechanical damage, or corrosion. They can exist in various forms such as open circuit, short circuit and ground fault. including: Open circuit will lead to reduced torque, increased vibration, and overheating. Short circuit causes excess current flow, overheating and potential damage to stator winding. Ground fault causes a leakage current that can trip circuit breakers or cause electrical shocks.

Rotor fault can arise from broken rotor bars, faulty end rings, or bearing wear. Broken rotor bars disrupts the rotor's magnetic field, causing excessive vibration, noise, and torque pulsations. Faulty end rings causes disruption in current flow and lead to similar symptoms as broken rotor bars. Bearing wear can cause the rotor to rub against the stator, resulting in noise, vibration, and increased friction, reducing the motor's efficiency.

B. Starting capacitor fault

The starting capacitors are critical components in single-phase induction motors, providing the necessary phase shift to start the motor. Faulty capacitors can hinder or prevent the motor from starting properly. Capacitor burnout occurs when the internal components fail, causing a loss of capacitance. This prevents the capacitor from providing the required phase shift for starting. Capacitor leakage occurs when the dielectric material between the capacitor plates deteriorates, allowing current to leak. This reduces the capacitor's effectiveness and can cause overheating. Capacitor misconnection can lead to incorrect phase shifts or voltage imbalances, preventing the motor from starting or causing it to run inefficiently.

C. Mechanical fault and thermal fault

Mechanical fault is classified into bearing wear, shaft alignment and bent shaft. Bearing wear can cause excessive vibration, noise, and friction, reducing the motor's efficiency and potentially leading to rotor damage. Shaft misalignment leads to excessive vibration and wear, reducing the motor's lifespan. Bent shaft causes imbalance and vibration, leading to premature bearing wear and motor damage.

Thermal fault is caused due to overloading, improper ventilation, high ambient temperature conditions – Overloading results in operating the motor beyond its rated capacity can lead to overheating and damage to the stator winding and rotor. Improper ventilation leads to trap the heat within the motor, causing overheating and potential insulation breakdown. Ambient temperature conditions operating the motor in high ambient temperatures can contribute to overheating, especially if ventilation is limited.

III. FAULT ANALYSIS OF SINGLE-PHASE INDUCTION MOTORS

The figures 1 and 2 show the simulink model and its output waveforms of split phase induction motor when subjected to line to ground fault. From the output waveforms, it is inferred that motor is subjected to line to ground fault at the time period 3secs.The speed,torque,auxiliary winding and main winding's currents are decreased. Especially the speed decreases drastically during this fault. The motor starts to rotate in reverse direction which causes a decreased efficiency and increased electrical and mechanical stresses. It should be avoided or else it will cause damage to the load.Hence, it is necessary to protect the motor.

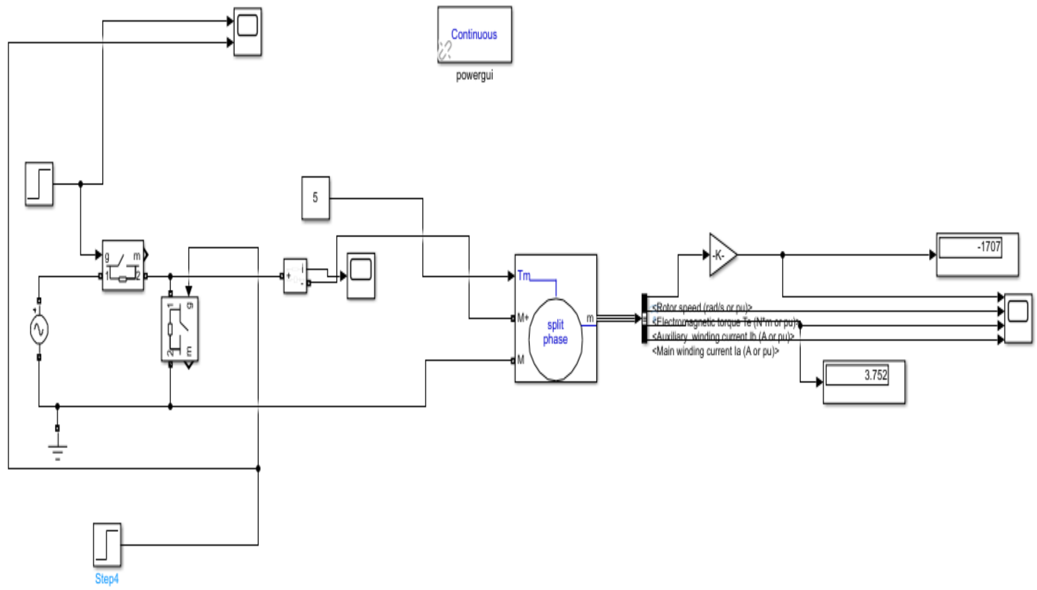

Fig.1. Simulink model of split phase induction motor when subjected to line to ground fault

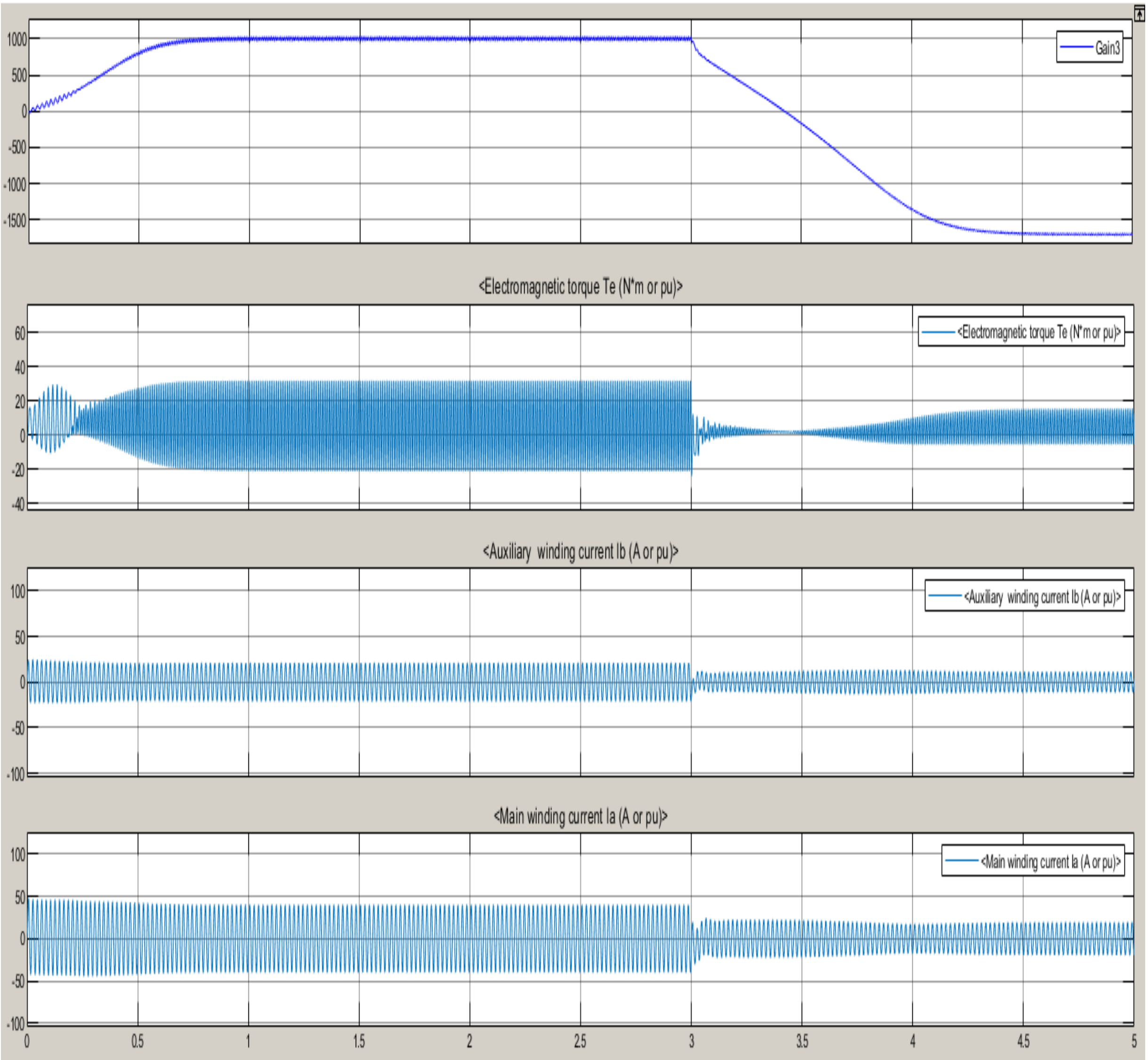

Fig. 2 Output waveforms of split phase induction motor

IV. FAULT PROTECTION CIRCUIT OF SPLIT PHASE INDUCTION MOTOR

The figures 3 and 4 show the simulink model of protection circuit and its output waveforms of split phase induction motor. The addition of a circuit breaker to an existing circuit, effectively prevents the motor from reverse rotation. The circuit breaker increases the motor's speed from -270 rpm to 748 rpm. Table 1 explains the fault analysis of split phase induction motor. During the fault, the speed decreases and torque, main winding current and auxiliary winding current drop to zero. After the clearance of fault, speed and main winding current are decreased to 30% and 44% respectively. Also, auxiliary winding current and torque are increased to 53% and 73% respectively. Table 2 explains the response of circuit breaker.

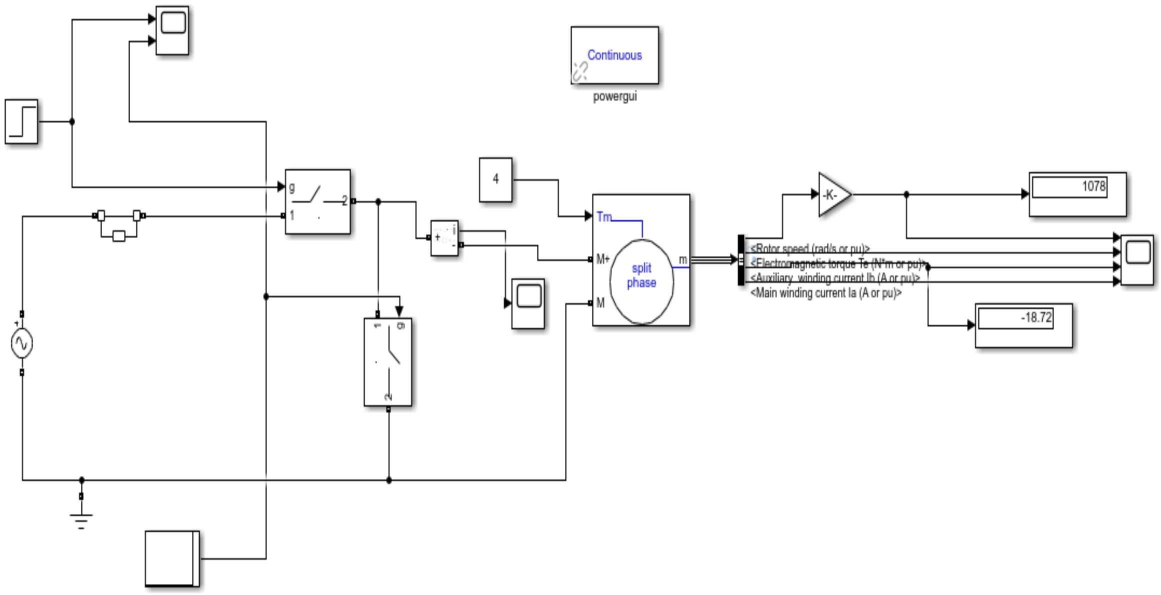

Fig. 3. Simulink model of protection circuit of split phase induction motor

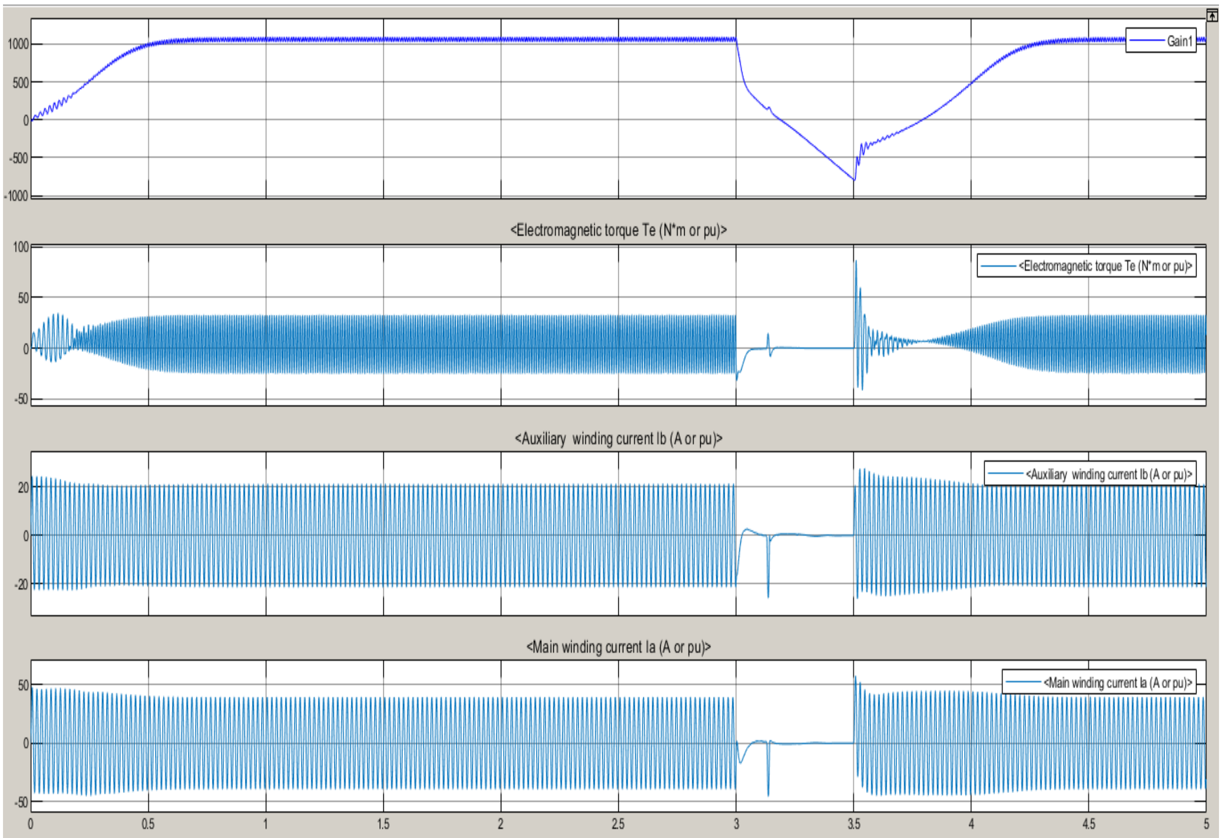

Fig. 4. Output waveforms of split phase induction motor protection circuit

TABLE 1 Fault analysis of split phase induction motor

Time(s)	Speed (rpm)	Torque (Nm)	Main winding current(A)	Auxiliary winding current(A)
Before fault At t=1.5s	1079	15	32	20
During fault At t=3.1s	-270	0	0	0
After fault (with circuit breaker) At t=4.5s	748	26	18	43

TABLE 2 Response of circuit breaker

Type of operation	Fault time(s)	Circuit breaker Operating time(s)	Speed recovery Time(s)
Instant	3	4	4.73
Delayed	3	6	8.65

From the table 2, it is evident that a faster operating circuit breaker results in a quicker restoration of motor speed, which in turn helps in the motor protection.

V. HARDWARE IMPLEMENTATION OF FAULT DETECTION AND CLEARANCE SYSTEM

The hardware implementation of the fault detection and clearance system which involves the integration of current, voltage, speed, and temperature sensors into an Arduino microcontroller. It will detect the faults and safeguard the electrical equipment from abnormal conditions. Figure 5 shows the block diagram of the proposed fault detection and clearance system. Figures 6 and 7 depicts the flowchart and hardware model of the proposed scheme respectively.

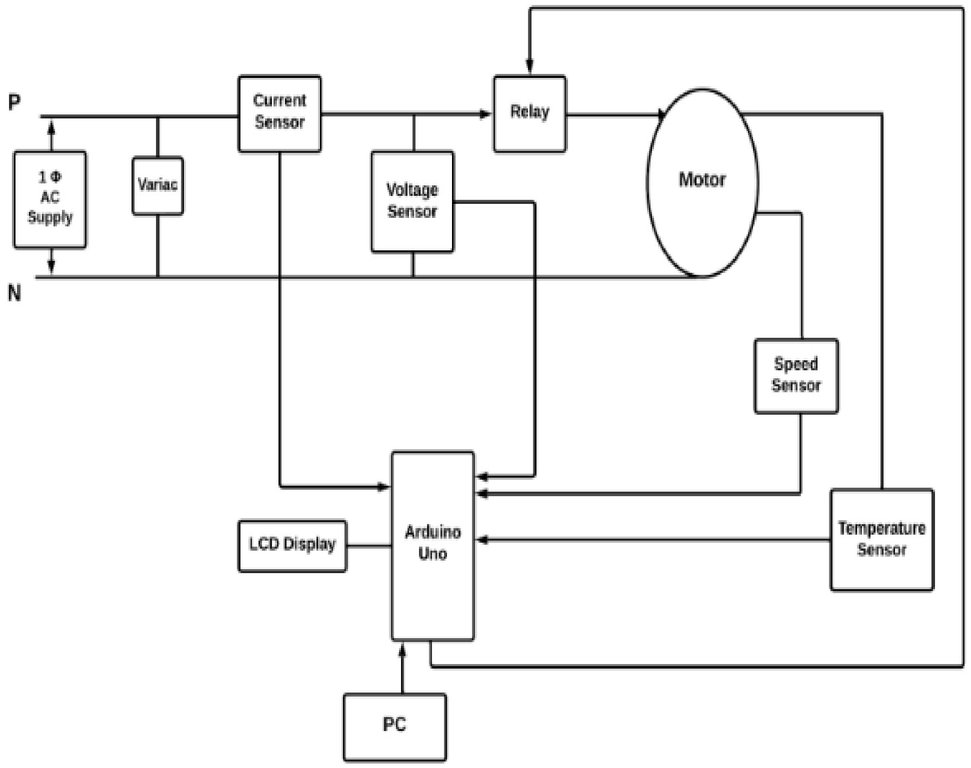

Fig.5. Block diagram of the proposed fault detection and clearance system

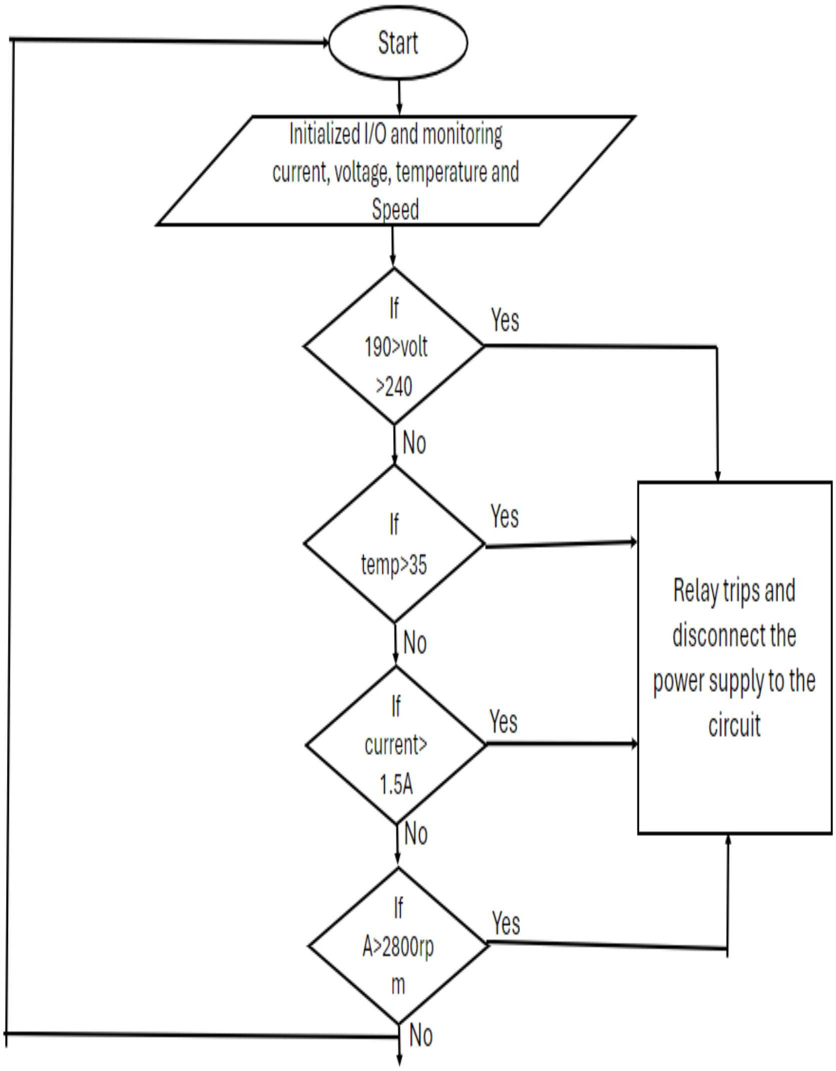

Fig. 6. Flowchart of the proposed scheme

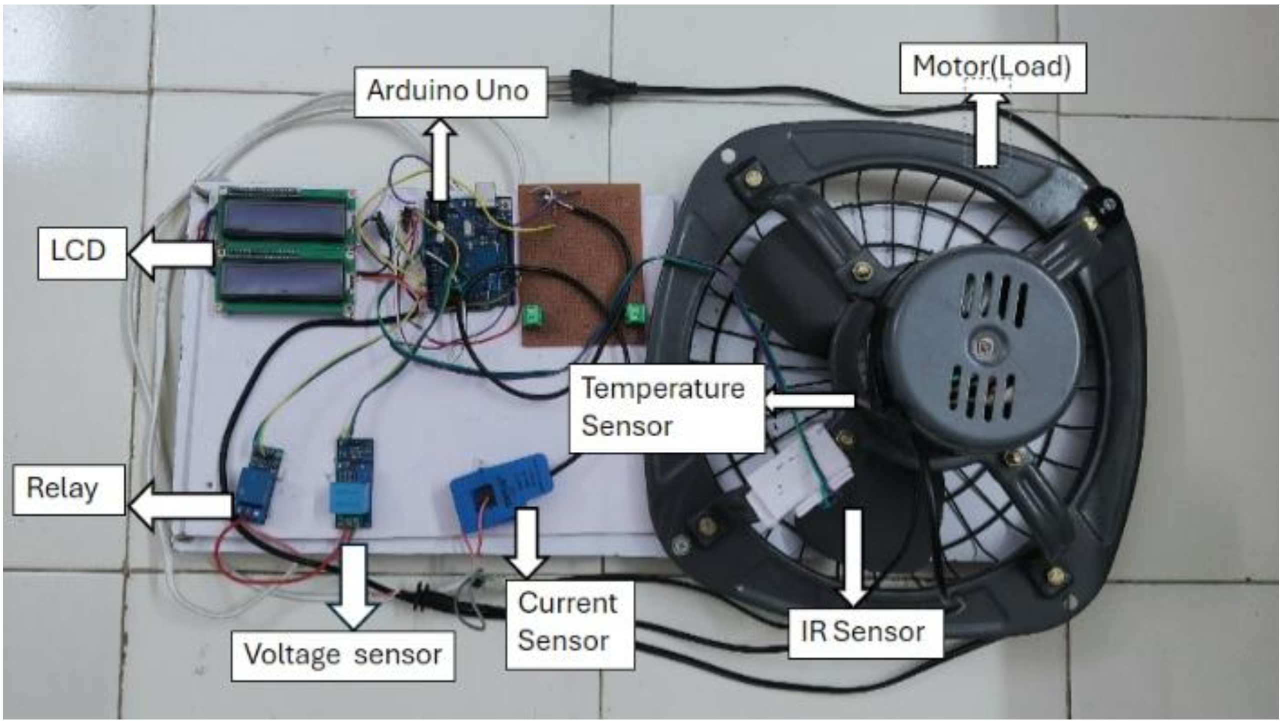

Fig. 7. Hardware model of the proposed scheme

D. Arduino Uno

The Arduino Uno is a microcontroller board based on the ATmega328P microcontroller chip. The figure 8 depicts the hardware model of Arduino uno. The specifications are: operating voltage: 5V ,input voltage (recommended): 7-12V, input voltage (limits): 6-20V , DC current per I/O Pin: 20 mA, DC current for 3.3V Pin: 50 mA ; memory: 32 KB and flash, 2 KB SRAM, 1 KB EEPROM.

Fig. 8. Arduino Uno

E. Relay module

A relay module serves as an interface between low-power electronic circuits, like those found in microcontrollers, and high-power or high-voltage devices, such as motors, lights, or appliances. By using relays, which are essentially switches operated by an electromagnet, The additional components like diodes, resistors, and transistors are often included to ensure proper operation, protect the circuitry, and enhance performance. The figure 9 shows the model of relay module . The specifications are: operating Voltage:5V ; Pins-Vcc, GND, IN ; Contact Rating: 10A at 250VAC or 30VDC

Fig. 9. Relay Module

F. Current Sensor (SCT013)

The SCT013 sensor is designed to be clamped around a conductor without the need for any physical contact with the live wires. It's especially useful in situations where it's not feasible or safe to disconnect the circuit for installation. The figure 10 shows the model of current sensor(SCT013). The specifications are: input current range: 0 to 100A or 0 to 30A, frequency range:50Hz to 60Hz, output Signal: 50 mA per 1A of AC current and accuracy: ±1.5%.

Fig.10. Current sensor (SCT013)

G. Voltage Sensor(ZMP101B)

The ZMPT101B voltage sensor is used for measuring AC voltage in electrical circuits.. The sensor outputs a voltage signal proportional to the input voltage, which can be scaled down for easy interfacing with microcontrollers or other electronic devices.The figure 11 depicts the model of voltage sensor (ZMP101B) .The specifications: are rated input current: 2mA ,rated output current: 2mA ;Linear range: 0~1000V 0~10mA ,isolation withstand voltage: 4000V ; and operating Frequency 50-50Hz.

Fig. 11. Voltage sensor (ZMPT101B)

H. Temperature Sensor (Thermocouple)

A thermocouple, comprising two metal wires, produces voltage proportional to temperature difference across its ends, known as the Seebeck effect. This voltage output serves as a measure of temperature, facilitating precise temperature sensing in various applications. The figure 12 depicts the model of thermocouple sensor. The specifications are : temperature ranges from -200°C to +1350°C (-328°F to +2462°F).

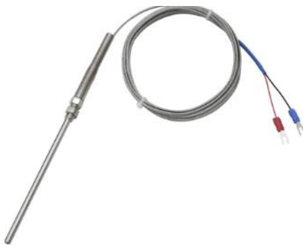

Fig. 12. Thermocouple

I. IR SENSOR

An IR sensor shown in figure 13 can measure the heat of an object as well as detect the motion. It is also used to measure speed by emitting infrared light towards an object and detecting the reflected light. As the object moves, the frequency of the reflected light changes due to the Doppler effect. By analyzing this frequency shift, the sensor can determine the speed of the object relative to the sensor's position.

Fig.13. IR sensor

J. Liquid Crystal Display

The main function of LCD technology is to display images and information by manipulating polarized light through liquid crystal molecules. By controlling the electric voltage applied to these molecules, LCDs can selectively allow or block light, creating the desired images and colors. The figure 14 shows the model of LCD.

Fig. 14. LCD

LOAD (SINGLE-PHASE INDUCTION MOTOR)

Single phase induction motors are used from ceiling fans to refrigerators and small machinery. These motors offer simplicity, reliability, and cost-effectiveness. Their versatility and ease of maintenance make them indispensable components of modern-day electrical systems. Figure 15 depicts the model of single-phase induction motor. The specifications are:rated voltage:230V, rated frequency:50 HZ, rated power:60 Watts and rated speed:1400/2800 rpm.

Fig.15. Load (single-phase induction motor)

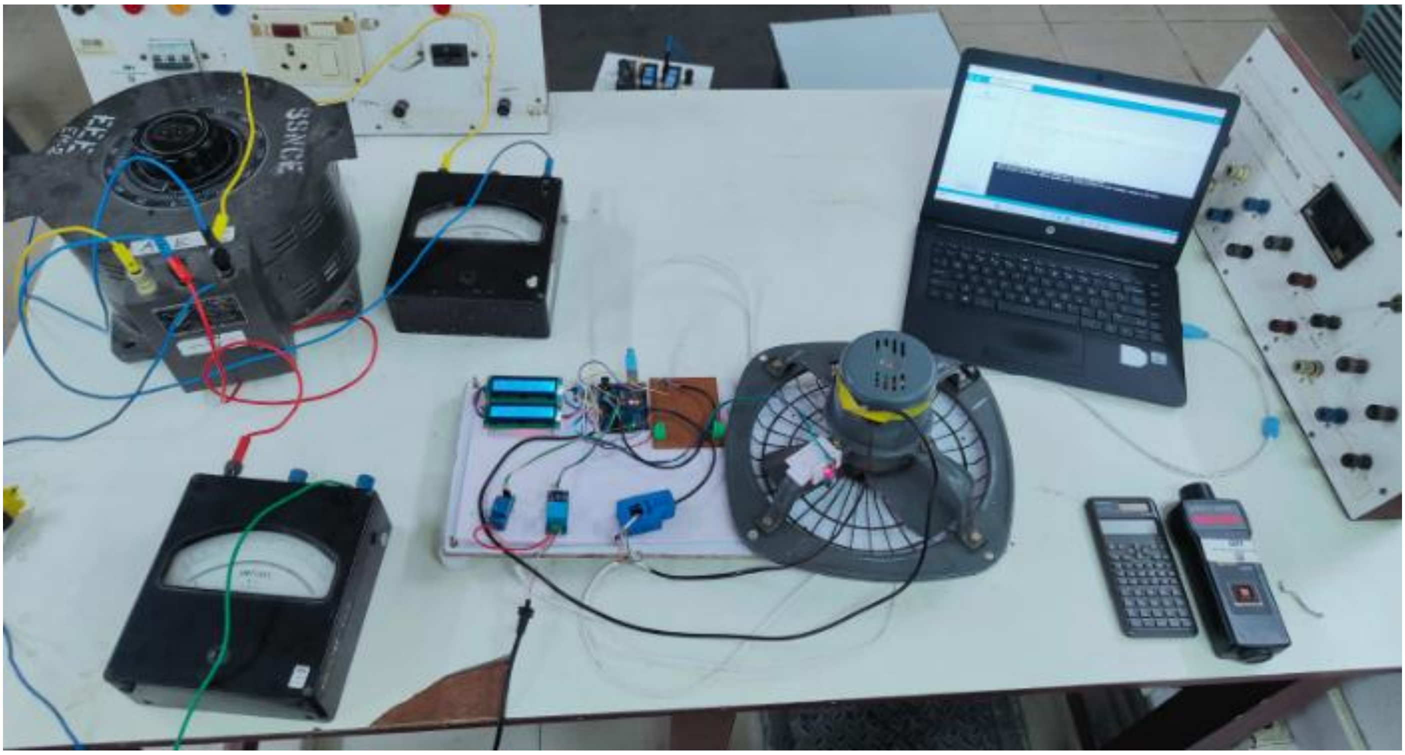

Fig.16. Hardware configuration

Figure 16 illustrates the comprehensive hardware configuration comprising sensors, an Arduino Uno, a relay module, and a motor serving as a load, LCDs for parameter display. The power supply is given to the motor, with connections to current and voltage sensors. Additionally, a relay is connected to the supply side which will disconnect power during abnormal conditions.

Temperature and IR sensors are attached to the motor for temperature sensing and speed measurement. The power supply to the Arduino is given through laptop and code is uploaded into it.

VI. GENERALIZED REGRESSION NEURAL NETWORK (GRNN)

A schematic diagram of the GRNN is shown in Figure 17. The GRNN consists of four layers such as an input , a pattern , a summation and an output. The input layer is connected to the pattern layer, where each unit represents a training pattern. The output is a calculation of the distance of the input from the stored patterns. Each pattern layer unit is joined to 2 neurons in the summation layer such as S-summation neuron and D-summation neuron. The earlier computes the sum of the weighted outputs of the pattern layer while the later calculates the outweighed outputs of the pattern neurons.

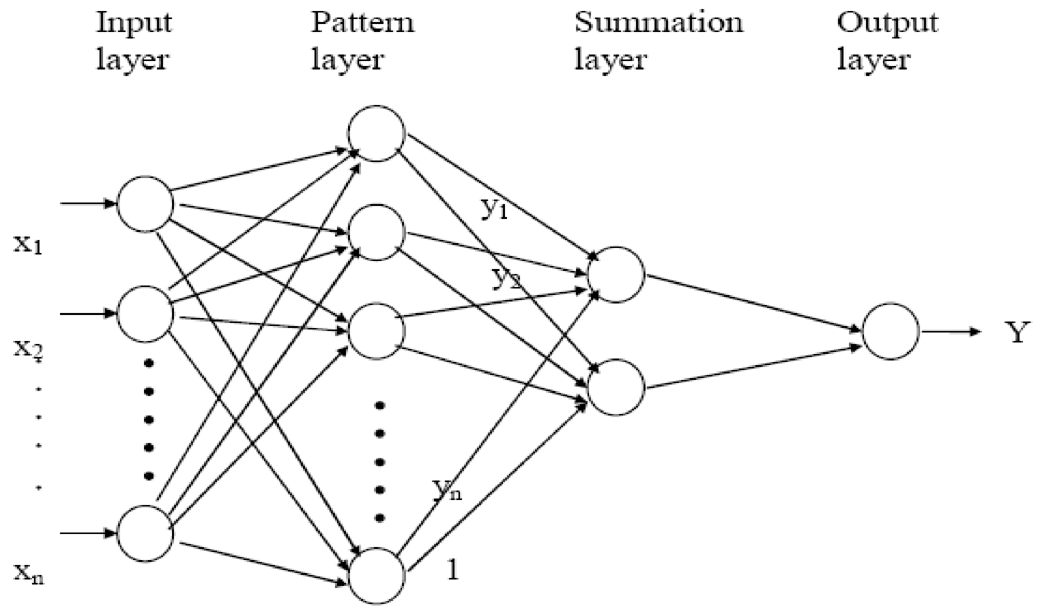

Fig. 17. Schematic diagram of GRNN

The connection weight between the i^{th} neuron in the pattern layer and the S-summation neuron is y_i. The target output value corresponding to the i^{th} input pattern. The D-summation neuron had unity connection weight. The output layer merely divides the output of each S-summation neuron by that of each D-summation neuron, yielding the predicted value to an unknown input vector x as

$$\hat{y}_i(x) = \frac{\sum_{i=1}^{n} y_i \exp[-D(x, x_i)]}{\sum_{i=1}^{n} \exp[-D(x, x_i)]} \qquad (1)$$

where n indicates the number of training patterns and the Gaussian D function is defined as

$$D(x, x_i) = \sum_{i=1}^{p} \left(\frac{x_j - x_{ij}}{\zeta} \right)^2 \qquad (2)$$

where, p indicates the number of elements of an input vector.

The terms x_j and x_{ij} represent the j^{th} element of x and x_i respectively. The term ζ is generally referred to as the spread factor. The GRNN method is used for estimation of continuous variables, as in standard regression techniques. It is related to the radial basis function network and is based on a standard statistical technique called kernel regression. The joint probability density function (pdf) of x and y is estimated during a training process in the GRNN. Because the pdf is derived from the training data with no preconceptions about its form, the system is perfectly general. The success of the GRNN method depends heavily on the spread factors. The larger that spread is, the smoother the function approximation. Too large a spread means a lot of neurons will be required to fit a fast changing function. Too small a spread means many neurons will be required to fit a smooth function, and the network may not generalize well.

The sequence of steps to be followed in GRNN training procedure are as follows.

Step:1 Read the input vector, input neuron

Step:2 Memorize the relationship between input and response

Step:3 Output is estimated using the transfer function,

$$\theta_i = e^{-\frac{(X-U_i)'(X-U_i)}{2\sigma^2}}$$

Step:4 Compute simple arithmetic summation,

$$S_s = \sum_i \theta i$$

Step:5 Compute weighted summation

$$S_w = \sum_i w_i \theta_i$$

Step:6 Output

$$Ouput = \frac{S_w}{S_s}$$

A. Proposed methodology and implementation with GRNN

The development of GRNN model to assess blend ratio has two major steps.

Step: 1 Generation of data pattern and training the GRNN

Step: 2 Testing of GRNN model with new data sets.

B. Data set generation

The input parameters strongly influence the performance of GRNN model. The model presented in this paper has the following as input parameters: Voltage, current, input power and losses. The output of GRNN model will be speed, torque, output power and temperature. The electro-mechanical parameters were measured using MATLAB simulation and constructed hardware. (section 2.2). Two combinations of electro-mechanical parameters have been formulated in order to check the suitability of GRNN in the performance analysis of induction motors..

Combination 1a: Input is P1 -Voltage in V , Output is T1- Speed in rpm.

Combination 1b: Input is P2- current in A; Output is T2-torque in N-m.

Combination 2a: Input is P3- Input power in W ; Output is T3- Output power in W

Combination 2b: Input is P4-losses in W; Output is T4-temperature in ˚**C.**

If input is voltage (195 V), then output is speed (1325 rpm)
If input is current (0.26 A), then output is torque (0.2275 N-m)
If input is input power (49.50 W), then output is output power (48.91 W)
If input is losses (0.596 W), then output is temperature (34.83 ˚**C**)

The above mentioned combinations of electro- mechanical parameters have been used to train the GRNN model. The output of GRNN model will be the speed, torque, output power and temperature. Then four data sets were generated with different electrical parameters to test the performance of proposed GRNN model. The GRNN model was tested using those 4 data sets. The MATLAB-Simulink model of combination 1 and 2 are shown in figures 18 and 19. The tables 3-a, 3-b and 4-a, 4-b give information about the training data for the combination 1a, 1b and 2a, 2b respectively.

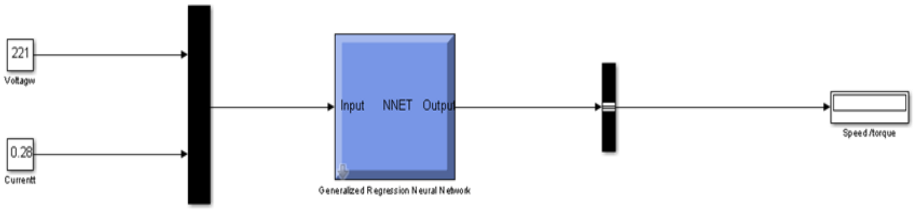

Fig. 18. MATLAB-Simulink model of combination 1

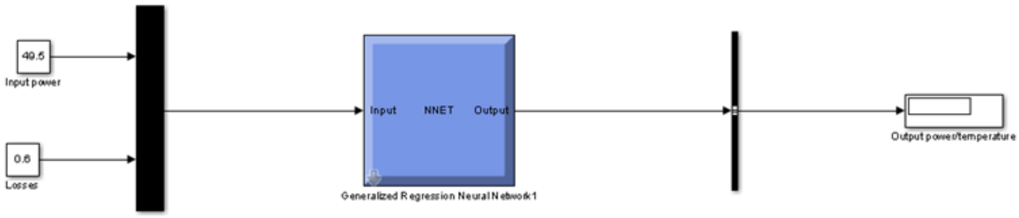

Fig. 19. MATLAB-Simulink model of combination 2

TABLE 3-a. Training data for combination 1a

Training data	Input 1 Theoretical voltage (V) V	Input 1 Practical voltage (V) V	Output 1 Theoretical speed (N) rpm	Output 1 Practical speed (N) rpm
TRA1	230	221	1678	1668
TRA2	200	203	1447	1581
TRA3	190	193	1203	1202
TRA4	180	183	882	911

TABLE 3-b. Training data for combination 1b

Training data	Input 2 Theoretical current (I) A	Input 2 Practical current (I) A	Output 2 Theoretical torque (T) N-m	Output 2 Practical torque (T) N-m
TRA1	0.31	0.28	0.28	0.28
TRA2	0.28	0.25	0.22	0.22
TRA3	0.26	0.23	0.21	0.21
TRA4	0.25	0.23	0.2	0.2

TABLE 4-a. Training data for combination 2a

Training data	Input 3 Theoretical input power (P_{in}) W	Input 3 Practical input power (P_{in}) W	Output 3 Theoretical output power (P_{out}) W	Output 3 Practical output power (P_{out}) W
TRA1	57	49.5	49.2	48.91
TRA2	44.8	40.6	33.34	36.42
TRA3	39.52	35.51	26.46	26.43
TRA4	36	33.67	18.37	19.08

TABLE 4-b. Training data for combination 2b

Training data	Input 4 Theoretical Losses (L) W	Input 3 Practical losses (L W	Output 3 Theoretical temperature(T) ˚C	Output 3 Practical temperature(T) ˚C
TRA1	7.84	0.59	34.63	34.8
TRA2	11.46	4.18	34.81	35
TRA3	13.06	9.08	35.19	35.4
TRA4	17.53	14.59	35.81	36

VII. RESULTS AND DISCUSSION

The tables 5-a, 5-b and 6-a , 6-b give information about the test data for combinations 1a,1b and 2a,2b of electro-mechanical parameters.

TABLE 5-a. Testing data for combination 1a

Testing data	Voltage (V) V	Speed (N) rpm	GRNN	Deviation	Error %
TES1S	195	1351	1325	-26	1.92
TES2S	185	1104	1043	-61	5.52
TES1P	198	1256	1392	136	10.83
TES2P	187	1083	1202	119	10.99

TABLE 5-b. Testing data for combination 1b

Testing data	Current (I) A	Torque (T) N-m	GRNN	Deviation	% Error
TES1S	0.27	0.22	0.23	0.01	4.55
TES2S	0.25	0.21	0.23	0.02	9.52
TES1P	0.25	0.22	0.23	0.01	4.55
TES2P	0.23	0.21	0.23	0.02	9.52

TABLE 6-a. Testing data for combination 2a

Testing data	Input power (P_i) W	Output power (P_O) W	GRNN	Deviation	% Error
TES1S	42.12	31.13	36.42	5.29	17
TES2S	37	24.28	26.42	2.14	8.81
TES1P	39.6	28.94	36.42	7.48	25.85
TES2P	34.41	23.82	21.94	-1.88	7.89

TABLE 6-b. Testing data for combination 2b

Testing data	Losses W	Temperature (T) ^{0} C	GRNN	Deviation	% Error
TES1S	10.99	34.74	35.19	0.45	1.3
TES2S	12.72	35.63	35.81	0.18	0.51
TES1P	10.66	34.74	35.19	0.45	1.3
TES2P	10.59	35.63	35.19	0.44	1.23

The figures 20,21,22 and 23 show the absolute error of AE1 (voltage-speed), AE2 (current-torque) , AE3 (input power-output power) and AE4 (losses-temperature) of data sets. The range of absolute error percentage of combination 1a and 1b are (1.92 to 10.99) and (4.55 to 9.52). The range of absolute error percentage of combination 2a and 2b are (7.89 to 25.85) and (0.51 to 1.23). Also, it is observed that combination 2a (TES1P) had highest absolute error percentage of 25.85. The lowest absolute error percentage of 0.51 is noticed in combination 2b (TES2S).

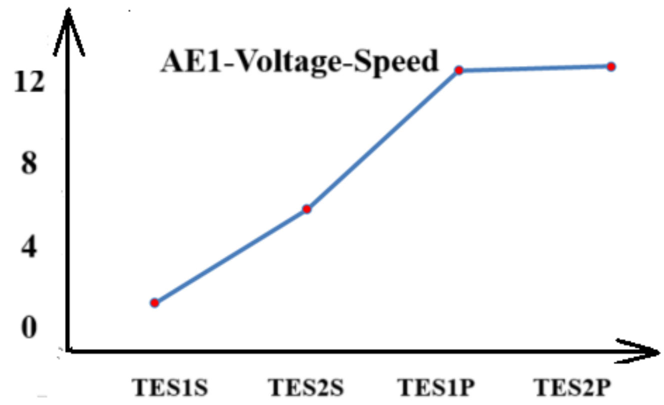

Fig. 20. Absolute error of voltage-speed of data sets

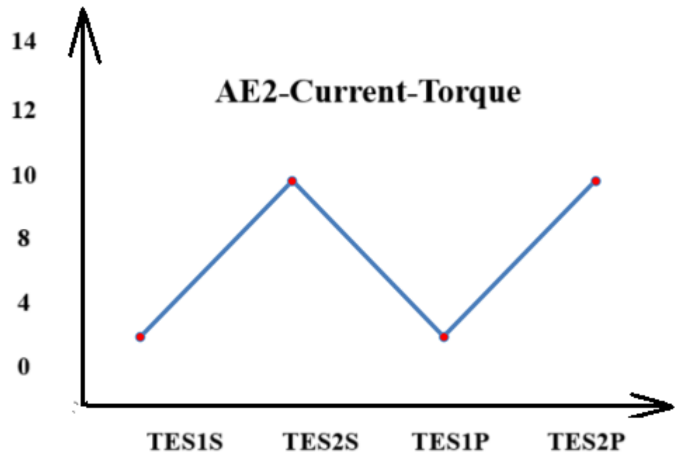

Fig. 21. Absolute error of current-torque of data sets

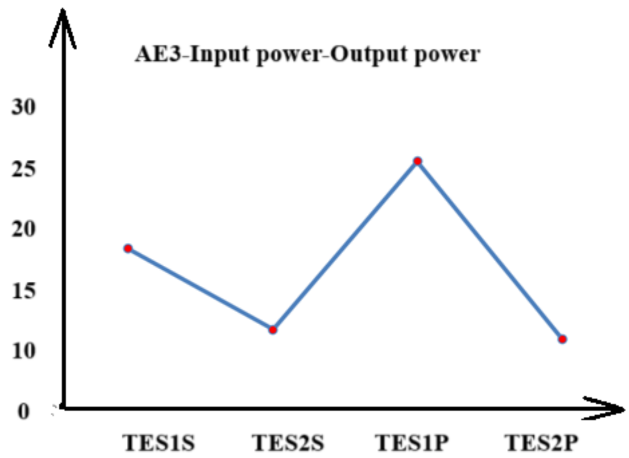

Fig. 22 Absolute error of input power-output power of data sets

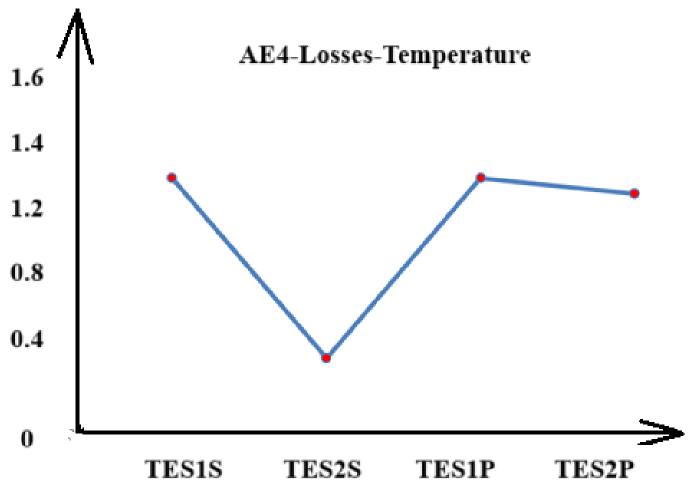

Fig. 23 Absolute error of losses-temperature of data sets

VIII. CONCLUSION

Fault detection and clearance system for electrical equipment has been implemented using Arduino Uno, current sensor, voltage sensor and relay module etc., Arduino Uno has been used to detect faults and showcases critical parameters on LCD. It also incorporated a relay module to safeguard the load by cutting off the power supply during abnormal conditions. fault detection and clearance system for electrical equipment has been implemented. This research discussed the applicability and suitability of GRNN for determining the electro-mechanical parameters of induction motor. The test results show that GRNN can be used for assessing the performance of induction motor. This reduces the cost, manpower and time involved in calculating the various electrical and mechanical parameters through the conventional tests. For this study, GRNN was applied to existing experimental data (simulated and hardware). To further improve the performance and the generalization property of the model, more input variables can also be incorporated in the system.

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